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OWNERSHIP NETWORKS EFFECTS OF SECURED BORROWING

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Ownership Networks Effects on Secured Borrowing[1]

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Abstract

The secured borrowing based on sell/buy-backs agreements is studied, specifically considering both: quantity and price. The empirical evidence presented in this paper suggests that, after controlling for specific individual characteristics, group-specific effects (defined by belonging or not to a financial group) play a relevant role in this market. Using spatial panel data models, we find that the amount of liquidity obtained with sell/buy-backs depend on traditional determinants (institution's size and financial leverage), but also, on the average size of the financial group to which the financial institution belongs. Similarly, the borrowing cost depends on the amount of liquidity, but the average profitability of the financial group is also significant. Our results are robust to different relationship structures specified for financial groups.

JEL: C33, G20, G32

Key words: funding costs, short-term liquidity, spatial panel data models

1. Introduction

The liquidity needs of financial institutions are usually given by the immediate payment obligations that they have acquired with their counterparties (Acharya and Merrouche, 2012). To meet these obligations, they can use their reserve balances at the central bank or the payments received from other institutions, but quite often they are forced to borrow liquidity in the money market, either from the central bank or from other financial institutions that are willing to lend their excess of funds. These loans may be secured or unsecured. The secured loans are represented by repurchase agreements (repos) and sell/buy-backs, while the unsecured are entirely composed by interbank loans.[5] Secured funding is conditioned to the provision of an

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[5] A sell/buy-back is a money market instrument that facilitates financial institutions' access to liquidity conditioned to the provision of an asset in guarantee for the loan. Sell/buy-backs differ from repos in that a discount to the market's value of the assets posted as collateral is not required, but also, in that the rate set for the loan is not explicit in the contract.

asset (collateral) that guarantees the repayment of the loan. As the debtor has an incentive to return to retake possession of the collateral, it has been considered that this asset reduces the risk of default (Kahn and Roberds, 2009). Thus, ceteris paribus, the collateral makes secured loans cheaper than unsecured ones.

Sell/buy-backs agreements are motivated by a participant's liquidity need, but they may also be driven by the necessity of a specific asset (buy/sell-back). In this context, and along the lines of Brunnermeier (2009), the fact that financial institutions can be lenders and borrowers at the same time, may be suggesting the existence of network effects in this type of agreements. Based on this premise, we investigate the role that ownership networks play on the short-term liquidity obtained by financial institutions.

Previous studies in the money market include approaches that have recognized the network effects on the access to short-term liquidity (Cocco, et al. 2009; Fecht et al. 2011, Afonso et al. 2014; Craig et al. 2015, and Martínez and León, 2015). On the cost side, Cocco et al. (2009) examine the effects that lending relationships have on the price of liquidity in the Portuguese interbank market. Afonso et al. (2014) study the formation of trading relationships in the overnight interbank market in the U.S., but also the effects that these relationships have on the pricing and provision of liquidity, and the transmission of liquidity supply shocks. Fecht et al. 2011, and Craig et al. (2015) analyze the price German banks pay for repos with the central bank. Fecht et al. (2011) found this price depends on the liquidity position of other participants, which underlines the role that financial relationships play on the borrowing cost by considering the price others pay for liquidity. Craig et al. (2015) used network topology measures to evaluate the effects of connectedness on banks' costs. Martínez and León (2015) coincide with these works in the relevance that financial relationships have on the borrowing cost in Colombia, specifically on sell/buy-backs operations.

This paper builds on the work of Martínez and León (2015) based on cross-section data, but we extend the analysis in four ways. Firstly, we examine the cost side of sell/buy-backs agreements as in the former study, but we additionally consider the quantity side with the aim to contribute to a better understanding of the liquidity obtained with this money market instrument. Secondly, we exploit the time-variation in data by employing spatial panel data models using recently-available data on sell/buy-backs rates. Thirdly, we estimate separate models for each type of agreements (over-the-counter, and based on counterparty quotas (MEC)). Finally, we evaluate a different criterion in the network effects (the former study considered the value of loans observed in the previous semester, while this study evaluates specifically the effects of financial groups). Our main results coincide with the former study and related literature in that the inclusion of network effects is of major importance to study the secured borrowing.

This paper contributes to the literature related to short-term liquidity, by considering the secured borrowing in the context of spatial econometric models, as an alternative way to understand the network effects in the money market. Previous studies have been focused on other money market segments (interbank loans and repos with the central bank) and have made use of other estimation approaches such as seemingly unrelated regressions system of equations (Cocco et al. 2009) and the Heckman selection model (Fecht et al. 2011, Acharya and Merrouche 2012, and Craig et al. 2015). Most of these studies examine the effects of lending relationships on the funding cost, through the inclusion of specific variables related to the lending (borrowing) activity or to network topology measures.

In contrast to these studies, our paper evaluates the effects of ownership networks on the liquidity obtained through sell/buy-backs, using spatial econometric models. An in-depth study of the networks effects generated by groups of institutions under common control on this market is interesting for the Colombian central bank, because it examines to what extent they may affect the amount of liquidity and the price at which it is obtained. Likewise, a deep understanding of sell/buy-backs is also relevant, as it may help to better comprehend the money market, and the transmission mechanism of the monetary policy through these agreements.

The effects of ownership networks are examined under the assumption that financial institutions may find low-cost liquidity (or more liquidity) when its group is considered financially strong. Hence, in addition to the source that provides the funds and the type of loans granted, the relationships with other market participants could also explain this market. We formally test this premise by evaluating the effects within financial groups from the quantity side (amount of liquidity), but also from the cost side (interest-rate spread). For this purpose, we implement the generalized method of moments (GMM) estimation with standard errors robust to heteroskedasticity and autocorrelation (HAC) to study this market, borrowing regression models from spatial econometrics to study this topic in the panel data context. After controlling for the market and individual-specific characteristics (institution's size, ROA, and financial leverage), we find that the liquidity obtained with sell/buy-backs operations also depends on group-specific effects generated by the average size (on the quantity side) and average profitability (on the cost side) of the financial group to which the institution belongs. Hence, to some extent, financial institutions that belongs to a financially strong group may get liquidity at more favorable interest rate spreads.

The rest of the paper is organized into six sections. In section 2, some basics on the secured and unsecured loans are briefly described with the aim of providing a more comprehensive view of short-term funding. Section 3 provides a detailed description of data and the variables used in the models' estimation, and sections 4 and 5 contain the estimation methodology and empirical results. Section 6 provides the conclusions and suggests directions for further research.

2. Secured lending markets

Financial institutions meet their payments obligations using the reserve balances they hold with the central bank or the payments they receive from their counterparties. But quite frequently, they are forced to borrow in the money market, either because they are short of funds, or because, following a precautionary motive in periods of uncertainty, they prefer to fund their payments using others' liquidity (Acharya and Merrouche, 2012). In any case, those with liquidity needs can resort to the unsecured market or to the secured market; a decision that depends, among many other things, on having an asset (or not) that can be pledged as collateral.

Access to liquidity in the secured market requires that the institution seeking funding delivers a collateral in guarantee for the loan. Therefore, these contracts are composed by the sale of collateral and an agreement to repurchase it at a specified future date (Choudhury, 2010). On the assumption that the borrower institution has an incentive to retake possession of collateral, it has also been accepted that this asset reduces the cost of keeping track of the borrower, as it secures the payment of the loan (Kahn and Roberds, 2009). This implies that if the borrower fails to pay, the lender can liquidate the loan by selling the collateral. Hence, the collateralized loans are usually cheaper than the non-collateralized.

The secured market is composed by repurchase (repo) agreements and sell/buy-backs. In a repo agreement the sale and re-purchase price is the same, and according to Choudhury (2010), the rate set for the loan (*repo rate*) is explicit in the transaction. Sell/buy-backs are a special type of repo, in which the sale and repurchase price of collateral do not coincide. The repurchase price includes the repo rate agreed in the contract, but also any further payment generated by collateral during the term of the contract (coupon payments). In repo transactions, the setting of an initial margin (*haircut*) on the collateral value protects the buyer against counterparty risk and the risk implied by collateral (variations in its market value, and illiquidity). Sell/buy-backs do not require that margin. These agreements may be motivated by a participant's liquidity need (sell/buy-back), or the necessity of a specific asset (i.e. buy/sell-back).

The fact that these agreements do not require initial margins (haircuts) suggests the existence of a risk component that may explain the price discrimination in this market. Besides, according to Gorton and Metric (as cited in Martínez and León, 2015), a perfect collateralization is not possible in markets with problems of adverse selection because the existence of informational asymmetries may generate counterparty risk. From a theoretical point of view, the access to liquidity with sell/buy-backs could be understood using the model of borrower-lending relationship proposed by Bester (1985) because it describes the optimal allocation of loans in markets with uncertainty and imperfect information. These two elements, generated by uncertain outcomes and heterogeneous borrowers, respectively, configure different levels of risk that the lender is not able to observe. Consequently, he sets up different contracts for each borrower's type to mitigate the effects that the informational asymmetries can have on his expected benefits (this model is briefly explained in Appendix A).

Bester's model is closely related to the market of sell/buy-backs, in which the financial institutions looking for funds are heterogeneous, and hence, the allocation of loans corresponds to an equilibrium given by different contracts. As in Bester's model, the type of institution looking for funds is not observable by the lender bank, who can use borrowers' observed variables when designing the terms of a loan contract (see Webb, 1991). These observed variables may be related to past information, such as institution's specific characteristics. We use these characteristics to control the informational asymmetry concerning the financial institutions that are looking for short-term funding.

Besides the theoretical implications described by the Bester's model, we also consider the premise that network effects may arise when financial institutions may be lenders and borrowers at the same time in the same market (Brunnermeier, 2009). This is precisely what happens with these agreements because a sell/buy-back for a financial institution is a buy/sell-back for its counterparty. Based on this proposition, we investigate the effects that financial groups may have on the sell/buy-backs market, considering both the quantity side (amount of liquidity) and the cost side (interest-rate spread). We assume that the amount of liquidity obtained (and its cost) depends on the market, specific effects given by individual characteristics (institution's size, profitability, and financial leverage), and group effects given by ownership networks.

3. The Data

Recent figures on short-term funding in Colombia reveal that during 2016 the secured loans represented around 91.0% of the total funding used by money-market participants, of which sell/buy-backs represented 48.4% while repos with the central bank 42.6%. In that same year, most of sell/buy-backs agreements were collateralized with sovereign bonds (98.7%), however, corporate debt and equity are also used in these transactions (Banco de la República, 2017).

Securities trading and transaction registration can take place in the Electronic Trading System (*SEN*) or in the Colombian Electronic Market (*MEC*). *SEN* is managed by Banco de la República, while *MEC* is managed by the Colombian Stock Exchange. In the *SEN* system, transactions are anonymous, and therefore, participants cannot identify each other when trading. Accordingly, the closing mechanism in this system is given by an automatic matching of the quoted interest-rates (price of liquidity), which occurs when a financial institution takes (accepts) the offer made by another participant. Alike the anonymous sell/buy-backs registered in the *SEN* system, the agreements in MEC require that the quoted prices (bid and offer) coincide; but they additionally require that the counterparty-quota (maximum amount to lend) determined for the financial institution asking for funds is binding. These counterparty-quotas are individually determined by financial institutions willing to provide liquidity, and are maintained fixed for a period. Thus, the sell/buy-backs registered in the MEC system are deemed semi-anonymous, which implies that financial institutions are not able to identify the counterparty of a transaction, but also, that closing mechanism is tied to the existence of a counterparty-quota that allows the transaction. Other sell/buy-backs are bilaterally transacted over-the-counter (*OTC*), and, as such, they contain perfect information from buyers and sellers (they know their counterparty when trading).

Before October 7, 2015, all participants of the sell/buy-backs' market kept exposures directly with one another until maturity. From that day on, the Colombian central counterparty (*CCC*) should take part on each operation registered in *SEN*, with the purpose of assuming the risk exposures at both sides of transaction, in what is called the *novation* process.[6] From January 18, 2016, the same change started to apply to the operations registered in *MEC*. Since then, all sell/buy-backs collateralized with sovereign bonds are processed through *CCC*. This study is focused on *MEC* and *OTC*, and hence, it covers the period July 2008 and December 2015, because there is not enough data to formally evaluate whether the entrance of the *CCC* in the clearing and settlement process in *MEC* led to changes in this market. This period contains around 2,500 observations of the agreements contracted by banks, financial corporations, commercial financing companies, brokerage firms, trust companies and pension funds.[7] We study sell/buy-backs of MEC and OTC separately, with the aim of capturing possible differences of institution's individual characteristics on the agreements contracted in a semi-anonymous way and over-the-counter. Within these data, we selected only the agreements that market participants contracted on their own behalf because they provide information about their individual liquidity needs.

Sell/buy-backs agreements are registered day by day; however, we use monthly data of the transactions for two reasons: first, not all financial institutions contract them daily, and second, the explanatory variables have a monthly frequency. The amounts of liquidity obtained with these agreements are presented in Figure 1.

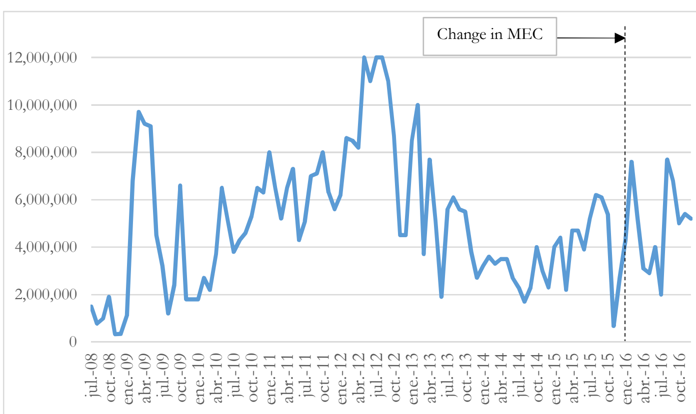

Figure 1. Total amount of sell/buy-backs (in million Colombian pesos). The total amount of sell/buy-backs is the sum of the liquidity value that financial institutions obtain through these agreements. The dotted line in December 2015 indicates the entrance of the Colombian central counterparty in the clearing and settlement process of the sell/buy-backs registered in the *MEC* system.

[6] The novation process reduces the counterparty risk because it implies the cancellation of a bilateral arrangement and its immediate substitution by two equivalent transactions: one between the central counterparty and the seller, and another between the central counterparty and the buyer (Cecchetti, Gyntelber and Hollanders, 2009).

[7] Investment management corporations and second-floor banks were excluded from the study because they operate exclusively on behalf of a third party.

As stated before, the funding cost with sell/buy-backs is not explicit in the contract, but it is implied in the forward price. Hence to calculate this cost, the spot and forward prices of collateral were compared. As in Martínez and León (2015), we use the central bank interest rate as a threshold to remove the agreements related to securities demand from data, under the assumption that only those with rates above the policy rate were contracted with the purpose to obtain liquidity. The agreements with rates below the policy rate have the purpose of obtaining the securities used as collateral. The borrowing costs correspond to the weighted average interest rates that were computed using the liquidity values as weights.

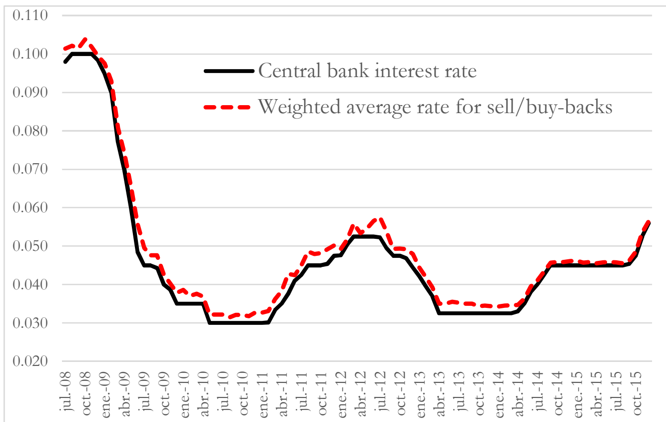

Figure 2. This figure displays the sell/buy-backs' rate (red dotted line) and the central bank rate prevailing at the end of each month (solid black line). The weighted average interest rate for sell/buy-backs (in annual terms) was obtained from comparing the spot and forward prices of each contract. As there may be several contracts in a month, this is the average rate weighted by the amounts of liquidity raised with sell/buy-backs. The rate displayed in this figure corresponds to the financial institution located at the median of the distribution. The central bank rate is established by that the Board of Directors of the Colombian central in their monthly meetings.

Another variable that may affect the borrowing cost is the central bank's interest rate, which is the same policy rate. In their monthly meetings, the Board of Directors of the Central Bank may set changes in this rate, in accordance with the inflation target. But given that this rate is not adjusted every month, it displays a stair-step behavior with upward and downward trends. The policy rate and the sell/buy-backs rate exhibit a similar behavior, where the latter typically follows the first rate (Figure 2). In model's estimation we use the interest-rate spread computed as the difference between the weighted average rate for sell/buy-backs and the policy rate prevailing at the end of each month (Figure 3).

To explain this market, we use traditional explanatory variables such as the institution's size, a profitability ratio, and the financial leverage, which were constructed using monthly information from the balance sheet that institutions report to the Financial Superintendency of Colombia (FSC). A table of summary statistics, including the dependent variables (liquidity amount and interest-rate spread) and explanatory variables is presented in the appendix (Table B1).

The size of financial institutions is defined as the natural logarithm of total assets, since this transformation places market participants in a measurement scale that facilitates comparisons between them. As usual, a positive relationship with the amount of liquidity and a negative relationship with the borrowing cost are expected, reflecting the advantages that institution's size should have on the access to short-term liquidity.

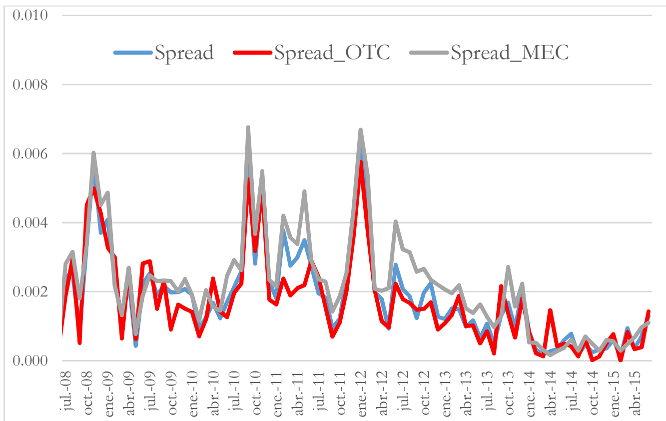

Figure 3. The interest rate spread is defined by the difference between the sell/buy-backs' rate and the central bank rate. The figure displays the interest-rate spreads of semi-anonymous transactions (MEC, gray line), transactions over-the-counter (OTC, red line) and both (blue line) for the institution located at the median of the distribution.

We include the return on assets (ROA) to evaluate the effect of institution's profitability in this market. This indicator is calculated in the Colombian Central Bank using information that institutions report to the FSC, and it is given by the ratio of net income to total average assets. Regarding this indicator, we expect to find a positive relationship with the liquidity amount, indicating that more profitable institutions will seek more liquidity with the aim of increasing their income and earnings. This positive effect could however be observed only if the liquidity cost is sufficiently smaller than an institution's profit.

The level of financing of each institution is given by the ratio of total liabilities and total assets. We expect to find a positive effect from this variable on the liquidity amount in the sense that highly leveraged institutions could be willing to seek more funding to cover their short-term liabilities. Based on the same argument, a positive relationship with the liquidity cost is conjectured as we assume that those with high leverage ratios will get higher rates.

The above-mentioned explanatory variables have been recognized in related literature as relevant factors to understand the liquidity cost. The size of financial institutions has been widely used in several studies (Craig and Fecht, 2007; Cocco et al. 2009, Fecht et al. 2011, Craig et al. 2015, and Martínez and León 2015), most of which coincide in that larger institutions obtain liquidity at more favorable rates. The ROA indicator has been considered as a proxy of financial health, and hence, a common result in these studies is that a worsening of ROA reduces the liquidity obtained (Cocco et al. 2009, Fecht et al. 2011 and Craig et al. 2015). The effects of financial leverage have also been studied under the notion that institutions more financially leveraged will be compelled to pay more for short-term liquidity (Martínez and León, 2015).

4. Estimation methodology

4.1 Linear panel data models

The benchmark model used for studying sell/buy-backs operations is given by the following equation:

$$Y_{it} = X_{it}^{T}\beta + \alpha_i + \varepsilon_{it}, \qquad (1)$$

where i denotes the institution's subscript (i=1, …, N) and t indicates the time (t = 1, …, T). The dependent variable Y_{it} is explained by the linear combination $X_{it}^{T}\beta$, the individual effects α_i, and idiosyncratic shocks ε_{it}, which are assumed to be orthogonal to the regressors X_{it} and individual effects α_i. This benchmark model can be stacked with respect to the institution index i and can be represented as:

$$Y_t = X_t\beta + \alpha + \varepsilon_t, \qquad (2)$$

where $Y_t = (Y_{1t}, \ldots, Y_{Nt})^T$, $X_t = (X_{1t}, \ldots, X_{Nt})^T$, $\alpha = (\alpha_1, \ldots, \alpha_N)^T$, $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})^T$, and finally, β represents the $K \times 1$ vector of unknown model parameters.

In equation (2), the dependent variable Y_t is a vector of observations (with dimension $N \times 1$) on the liquidity obtained or funding cost of financial institutions at time t; the liquidity amount is defined in natural logarithms, whereas the funding cost is defined as the interest-rate spread. This variable Y_t is assumed to be a function of a $N \times K$ matrix X_t that contains the K explanatory variables and of the unobservable individual effects α and error term ε_t (both of dimension N $\times$ 1). As described in Section 3, X_t contains monthly dummy variables that account for time-fixed effects, the interest-rate spreads, institution's size, ROA and financial leverage.[8] The sell/buy-backs will be studied also from the cost side: when modelling the interest-rate spreads and explanatory variables X_t will instead contain the liquidity amounts.

As we mentioned before, it is reasonable to expect network effects when, at the same time, financial institutions are lenders and borrowers (Brunnermeier, 2009). This market may be considered as a perfect example of that situation, in the sense that a sell/buy-back contract for an institution represents a buy/sell-back for its counterparty. The linear panel data models fail to consider the effects that such relationships could have on these agreements, and hence, these models may suffer from omitted variable bias (LeSage, 2014). Therefore, alternative specifications more comprehensive than linear panel data models should be evaluated. Specifically, we will consider spatial econometric models to analyze the effects of ownership links on secured loans. Nevertheless, given that linear panel data models are nested within the spatial counterparts, they will be used as benchmarks to compare the results obtained from spatial specifications.

4.2 Spatial Econometric models

Little attention has been paid to the network effects not related to measures of physical distance. Although there is no way to quantify the distance between a pair of financial institutions, it is true that the degree of proximity plays a major role in lending relationships. Hence, with the aim of providing a proper framework to analyze sell/buy-backs, we evaluate the effects of the spatial dependence arising from the links between financial institutions in terms of financial groups. Accordingly, we hypothesize that the cost and liquidity amounts that each institution assumes and obtains may also depend on the financial group they belong to. We believe that there could be unobserved influences generated by financial groups that may contribute to explain these agreements. Therefore, we build our premise based on the assumption that institutions may possibly obtain liquidity at a lower cost when its group is considered financially strong.

[8] The time-fixed effects, included to exploit the within group variation over time, are necessary in this setting to control for any seasonal effect that may have an impact on this market.

4.2.1 The effects of financial groups

To capture the effects of groups under common control in spatial econometric models, a weight matrix that characterizes the connections among institutions is required. This weight matrix W is a square $N \times N$ matrix and it reflects the existence (or absence) of connections between pairs of financial institutions. In the simplest case of the contiguity weight matrix, an element W_{ij} of W will be equal to one if institution i pertains to the same owners group as institution j; otherwise, that element will be zero. Other elements that take a value of zero are those located on the diagonal of the matrix (W_{ii}) because they correspond to the same institution; hence, defining a connection of an entity with itself is ruled out in this setting. Note that weight matrices will be row-normalized before entering the model(s) below. Finally, the weight matrices we use are constant over time given that the financial groups have presented very few changes during the sample period (see Section 5.2.1).

Recall now that the benchmark model in (2) was written as, for $\eta_t = \alpha + \varepsilon_t$,

$$Y_t = X_t\beta + \eta_t, \tag{3}$$

while the idiosyncratic errors in ε_t are mutually independent, the individual effects α (i.e., individual heterogeneity) may play a more complex role in the liquidity obtained in the sense that they could possibly affect a financial institution's borrowing depending on the group to which the institution belongs. Hence, we derive a network dependent specification assuming, as in LeSage and Pace (2009), that a part of the unobservable component η_t follows a spatial autoregressive process ($\varrho W \ \eta_t$), another part is correlated and can be explained by the explanatory variables X_t, and the rest is formed by independent and identically distributed noise ε_t (which is again a $N \times 1$ of random mutually independent errors):

$$\eta_t = \varrho W \eta_t + X_t \gamma + \alpha + \varepsilon_t \,. \tag{4}$$

Reorganizing the parameters and denoting by I_n the $N \times N$ identity matrix, it follows that

$$(I_n - \varrho W)\ \eta_t = X_t \gamma + \alpha + \varepsilon_t \tag{5}$$

and

$$\eta_t = (I_n - \varrho W)^{-1} X_t \gamma + (I_n - \varrho W)^{-1} (\alpha + \varepsilon_t). \quad (6)$$

Substituting this result into equation (3) and multiplying by $(I_n - \varrho W)$ results in the Spatial Durbin (SD) model,

$$Y_t = \varrho W Y_t + X_t (\beta + \gamma) + W X_t (-\varrho\beta) + \alpha + \varepsilon_t , \quad (7)$$

which includes network (spatial) effects both in the dependent variable (WY_t) and in the explanatory variables (WX_t). The former effect measures the spatial average of the liquidity obtained by other financial institutions pertaining to the same group, while the latter evaluates the average effect generated by the factors included in the set of explanatory variables. The scalar parameter ϱ measures the spatial lag of the liquidity amount, which assesses the degree of spatial dependence.

Reparametrizing the model by $\beta + \gamma \rightarrow \beta$ and $-\varrho\beta \rightarrow \theta$, the SD model can be expressed as

$$Y_t = \varrho W Y_t + X_t\beta + W X_t\theta + \alpha + \varepsilon_t . \quad (8)$$

Thus, the data generating process includes fixed effects and the institution's individual characteristics in X_t, but also the network effects induced by the dependent variable and the explanatory variables. The former network effect is given by the spatial autoregressive parameter ϱ and the average value of the liquidity obtained by other institutions in the group Y_t defined by the weights matrix WY_t. The latter network effects WX_t include the influence of market (cost of liquidity when the equation explains the liquidity amount; the borrowing cost, otherwise) and other institution specific covariates.

The SD model nests several other specifications, which can be seen imposing restrictions on the parameters.[9] If the network effects from explanatory variables are absent (θ=0), the SD model will collapse to a space lagged autoregressive process (SAR model):

$$Y_t = \varrho W Y_t + X_t\beta + \alpha + \varepsilon_t. \quad (9)$$

Likewise, in absence of the network effect induced by the dependent variable (ϱ=0), the SD model will collapse to the spatial lag of X (SLX) model:

$$Y_t = X_t\beta + W X_t\theta + \alpha + \varepsilon_t, \quad (10)$$

[9] The linear panel data model can be considered as a special case of the SD model that arises when both kinds of network effects are non-existent (ϱ=θ=0).

which is a local spillover specification as it implies that the impacts only affect the financial institution directly connected to the participant under study (institution i). In contrast, the SAR and SD models are global spillover specifications that, according to LeSage (2014), provoke feedback effects (*"the impacts affect neighboring regions, but also neighbors to the neighboring regions, neighbors to the neighbors, and so on"*, page 15).

4.3 Estimation method

According to Anselin, Le Gallo, and Jayet (2008), the estimation of spatial econometric models must deal with two specific issues: the endogeneity of the spatial lag and the non-spherical nature of the error variance-covariance matrix. The maximum likelihood principle and method of moments' techniques have been the most commonly used for the estimation of spatial models. Unlike the maximum likelihood (ML) method, the generalized method of moments (GMM) is preferred when the model includes time effects and non-row normalized spatial weights matrix, as in spatial dynamic panel data models; and it is computationally simpler (Lung-Fei and Yu, 2014). This last advantage is commonly related to the fact that the ML estimation method requires the computation of the determinant of the Jacobian matrix of the likelihood function for a spatial model, which may be difficult when the cross-sectional dimension N is large. In fact, the computation of this matrix and its determinant have been considered as the main obstacles for its implementation (Anselin et al. 2008). Moreover, the GMM has also been proven to produce robust estimations in the presence of non-spherical errors and allow us to deal with the possibly endogenous variables.

In the rest of the paper, all reported estimates are relying on the two-step GMM, using the two-stage least squares in the first step and the estimated optimal weighting matrix in the second step. Given that data exhibit heteroscedasticity and first- and second-order autocorrelation (see Section 5), the weighting matrix and standard errors are accounting both for heteroscedasticity and autocorrelation (GMM-HAC) following the procedure of Newey-West (1994). In both cases, the covariance structure is estimated using the Bartlett kernel with the pre-specified bandwidth of three lags (months) to correct for the time autocorrelation of residuals.

5. Empirical results

Let us mention some results of the initial diagnostic tests before discussing the model estimates. We first test for heteroscedasticity, executing White tests (without cross-products) on the residuals of the standard panel data models: the p-values below 5 per cent in all models indicate the presence of heteroscedasticity (Table B2 in the Appendix). Further, we examine the time autocorrelation functions of the residuals and find evidence of the strong first-order autocorrelation and weak second-order autocorrelation. As these results identify non-spherical errors, we computed the Newey-West standard errors robust to the existence of heteroscedasticity and serial correlation and reported them always in the parenthesis below estimates. The detected serial autocorrelation has also influence on the selection of instruments: given the (time-invariant) spatial correlation among the financial institutions, the instruments are in all cases taken as the past values of the respective explanatory variables, and therefore, at least second, but preferably third and higher lags should be used as instruments.

Given this instruments choice, we test for the endogeneity that may arise when quantities and prices are considered under the same structural model. To this end, the difference-in-Sargan C statistics is applied in all models previously introduced in Section 4 under the fixed effects assumption (e.g., see Hayashi, 2000, p. 220). To conduct this test, we instrument the interest-rate spread in the quantity models by a function of its own past values lagged by three and four months, which are uncorrelated with the contemporaneous liquidity cost. Analogously, we followed the same strategy to test endogeneity of liquidity quantity in the cost equations, where the liquidity amount is instrumented by its third and fourth lags. Our results do not provide any evidence supporting the existence of the endogeneity problem in the specifications (Table B3 in the Appendix). The absence of endogeneity could be attributed to the fact that these contracts depend on a liquidity management that vary from one financial institution to another, but mostly rely on financial indicators. In MEC these agreements are subject to credit limits (counterparty quotas) pre-determined by the lenders, which may remain fixed for some time.

Regarding the selection between models, the traditional Hausman test cannot be used in this context because the standard random effects model is not fully efficient due to the presence of autocorrelation and cross-sectional heteroscedasticity. However, the results obtained from the fixed and random effects specifications in Tables 1 and 2 do not yield similar coefficients, which provides evidence in favor of the fixed effects model. Yet another reason to select these models comes from intuition: the heterogeneity that exists among financial institutions, which may arise from specific factors such as their relative importance within the market (institution's size) and the business type they conduct. Nevertheless, we report results for both the random and fixed effect models for reference purposes.

The remainder of this section contains first the results obtained from linear panel data models, followed by the results from spatial econometric models considering two relationships structures for financial groups. We first assume that all financial institutions within a group are regarded as equal (0-1 weights before normalization), and latter, that their relative importance depends on their participation in the group's size (weights proportional to the relative share on the group's assets).

5.1 Traditional determinants of the secured market

From the quantity side, this market is examined by modelling the log-liquidity Y_t in equation (1) as a function of the interest-rate spread and other covariates. The obtained results for MEC as well as OTC, indicate that the amount of liquidity financial institutions obtain in this market decreases with the interest-rate spread, and increases with the institution's size and its leverage ratio (Table 1).

Table 1. Linear panel data models for liquidity

	MEC	MEC	OTC	OTC
	Fixed effects	**Random effects**	**Fixed effects**	**Random effects**
Spread	-56.12	-32.36	-42.58	-55.65
	(12.48)***	(19.90)	(11.43)***	(13.19)***
Institution's size	0.1982	-0.1937	0.8018	-0.0293
	(0.1099)*	(0.0357)***	(0.1363)***	(0.0311)
ROA	-0.3592	0.4750	0.3453	0.5869
	(0.2278)	(0.1319)***	(0.4160)	(0.3666)
Leverage	3.20	3.63	1.03	2.67
	(0.3747)***	(0.2732)***	(0.4699)**	(0.2880)***
Constant		24.13		22.65
		(0.5034)***		(0.4906)***
Including month effects	Yes	Yes	Yes	Yes
Number of observations	1,936	1,936	1,850	1,850
R-squared	0.3489	0.2614	0.2150	0.1975

Robust standard errors computed using GMM-HAC in parenthesis.
*, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Regarding the interest-rate spread, the estimated coefficient exhibits the expected negative sign, indicating that a widening of this spread will reduce the institution's willingness to borrow through sell/buy-backs, which could rise the institution's preference for other liquidity sources (interbank loans or repos with the central bank).

The financial institution size and leverage ratio are positively related to the amount of liquidity obtained. According to intuition, larger financial institutions may exhibit liquidity needs higher than that observed in other market participants, presumably because they must make larger payments. Likewise, financial institutions with high leverage ratios may need more liquidity to finance their short-term liabilities.

On the cost side, the results indicate for MEC and OTC that the quantity and the borrowing cost are negatively related, which, holding all else equal, indicates that sizable loans could represent cost reductions for institutions with liquidity needs (Table 2).

Table 2. Linear panel data models for the borrowing cost

	MEC	**MEC**	**OTC**	**OTC**
	Fixed effects	**Random effects**	**Fixed effects**	**Random effects**
Liquidity	-0.00030	-0.0001092	-0.00020	-0.0001706
	(0.00010)***	(0.000082)	(0.000079)***	(0.000049)***
Institution's size	-0.0010890	-0.0005	-0.0000008	-0.0006
	(0.00038)***	(0.000052)***	(0.00030)	(0.000040)***
ROA	-0.000125	-0.00003	-0.0009	-0.0033
	(0.00061)	(0.0003)	(0.00127)	(0.00080)***
Leverage	0.0026	0.0015	0.0003	0.0017
	(0.0010)***	(0.000391)***	(0.00112)	(0.000465)***
Constant		0.01011		0.01278
		(0.0022)***		(0.00138)***
Including month effects	Yes	Yes	Yes	Yes
Number of observations	1,936	1,936	1,850	1,850
R-sq	0.243	0.260	0.1576	0.3026

Robust standard errors computed using GMM-HAC in parenthesis.
*, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Other traditional determinants that are relevant predictors of the agreements registered in MEC are the institution's size and the leverage ratio.[10] The effect of institution's size on the borrowing cost is negative, which coincides with previous studies that have pointed out the advantages that this variable represents in the money market (Cocco et al. 2009, Fecht et.al 2011, Craig et al. 2015, and Martínez and León 2015). This result suggests that larger institutions may obtain liquidity at rates lower than other market participants. In this same line, the financial leverage is also relevant, indicating as expected, that highly-leveraged institutions will have to pay more for short-term liquidity.

[10] We estimate models for the borrowing cost including the policy rate in the set of explanatory variables. The estimated coefficient (close to one) suggests that changes in this rate are to a large extent transmitted to other short-term rates (there is an almost perfect pass-through).

5.2 The effects of financial groups on sell/buy-backs market

In Colombia, financial groups operate as decentralized organizations structured as holding companies that include banks and non-bank financial intermediaries. And although these groups are predominantly based on banking activities, they may also include firms dedicated to securities, investment, and insurance activities. To account for the effect that the groups of companies under common control may have on this segment of the money market, we use public information to classify the market participants in financial groups.[11] As a result, we identify close to thirty-three institutions related to financial groups. The same grouping was obtained from classifying institutions using information of the shareholder composition.

In the context of spatial econometrics, the institutions that do not pertain to a specific group can be considered as "islands" because they operate as separate units according to the defined weights. We specify two weight matrices: one with binary weights, and another with weights corresponding to the institution's individual participation in group's total assets prior to the row-normalization. Given the similarity of the qualitative results for these two specifications, we will focus on the quantitative interpretation only for the latter one.

5.2.1 Using a binary weights matrix

First, we construct a contiguity weight matrix W with elements that only identify the institutions as belonging or not to a specific group. This matrix is binary, with elements equal to one for the institutions pertaining to a specific group or zero for those not related to any group. Such a matrix with binary weights is not proper for estimating spatial econometric models since it should be row-stochastic (the sum of all the elements on a row should be equal to one, see LeSage and Pace, 2009). Therefore, we construct a row-normalized version of this matrix, which is symmetric because it assigns an equal weight to each institution belonging to the same group (Figure 4). Note that higher-order relationships (spatial lags) are not considered because a financial institution pertaining to a group cannot belong to another group.

We estimated static spatial econometric models to account for the network effects generated by the financial groups. These models are estimated under the assumption that the spatial weights

[11] We use the list of financial groups that appear in the editorial note of *Revista del Banco de la República* No. 1023 (2013).

matrix W is exogenous and fixed, where this last characteristic implies that there are no changes in the weights used within each group over time. We maintain constant this classification given that the processes of mergers and acquisitions observed within the sample period only represent changes for three institutions and have negligible effect on estimates. In two cases, an acquisition process was conducted, while in the last case, two institutions were merged.

Henceforth, besides the explanatory variables that were considered in the baseline regressions (the market and the individual specific effects), we now include group-specific effects WX_t capturing the network effects existing from financial groups. These effects include the institution's size, ROA, and financial leverage.

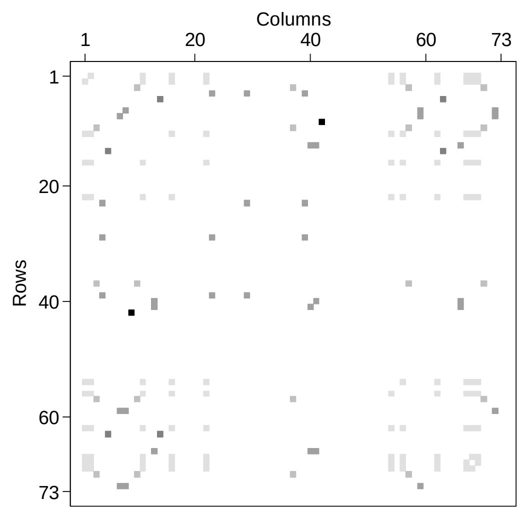

Figure 4. The binary weight matrix after normalization summarizes the financial groups, identifying the institutions owned by the same owners. Thirty-three financial institutions are related to financial groups, while the remaining forty operate separately. Each institution belonging to a group is marked with a one, while the others are marked with a zero. After row-standardization of the matrix, the institutions pertaining to a group get the same weight, which means they are considered equally important within the group.

Our estimation strategy goes from general to specific, considering the SD model first and more restrictive SAR and SLX specifications latter depending on parameters significance. The results for the SD model on the quantity side reveal that the spatial lag of the dependent variable (liquidity amount) is not significant, which supports the pure spatial lag of X model (Table 3).

For MEC as well as for OTC the results validate the relevancy of traditional determinants of liquidity amounts (interest-rate spread, institution's size and financial leverage (Table 1)), but they additionally identify a positive group effect generated by the average size (W_Institution's size). Hence, ownership networks provokes a positive local spillover effect on the quantity side of the market, favoring institutions that belong to financial groups with a large assets size.

Table 3. SLX models for Liquidity

	MEC	MEC	OTC	OTC
	Fixed effects	**Random effects**	**Fixed effects**	**Random effects**
Spread	-55.95	-39.25	-44.39	-57.16
	(12.43)***	(17.32)**	(11.68)***	(13.17)***
Institution's size	0.2172	-0.1145	0.8680	0.0067
	(0.1103)**	(0.0370)***	(0.1357)***	(0.0344)
ROA	-0.3408	0.5135	0.3522	0.6625
	(0.2279)	(0.1309)***	(0.4162)	(0.3582)*
Leverage	3.15	3.11	0.8397	2.48
	(0.3754)***	(0.2759)***	(0.4709)*	(0.2907)***
W_Institution's size	0.0881	-0.0520	0.0972	-0.0227
	(0.0313)***	(0.0081)***	(0.0424)**	(0.0095)***
Constant		23.67		22.36
		(0.5160)***		(0.5018)***
Including month effects	Yes	Yes	Yes	Yes
Number of observations	1,936	1,936	1,850	1,850
R-squared	0.352	0.288	0.221	0.202

Robust standard errors computed using GMM-HAC in parenthesis.
*, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

As in the models of amounts, we use the SLX model to study the borrowing cost of these agreements. The space-time panel data estimations (Table 4) corroborate previous results on the negative effects of the amount of liquidity in OTC and MEC. But in this last case, the institution's size and financial performance (i.e. financial leverage) are also relevant predictors of the borrowing cost. Hence, a unit change in institution's size still generates cost reductions, while a marginal change in its leverage ratio exerts the opposite effect.

Table 4. Spatial models for the borrowing cost

	MEC	MEC	OTC	OTC
Spread	**Fixed effects**	**Random effects**	**Fixed effects**	**Random effects**
Liquidity	-0.00030	-0.00014	-0.00021	-0.00018
	(0.00011)***	(0.000079)*	(0.000081)***	(0.000048)***
Institution's size	-0.0011	-0.0005	0.0001	-0.0005
	(0.00039)***	(0.000064)***	(0.000312)	(0.000055)***
ROA	-0.000114	-0.0001	-0.0009	-0.0032
	(0.00061)	(0.00031)	(0.00127)	(0.00079)***
Leverage	0.0025	0.0012	0.0001	0.0015
	(0.00105)***	(0.00043)***	(0.001115)	(0.00054)***
W_Institution's size	0.00015	0.000159	0.00013	-0.000023
	(0.000095)	(0.000055)***	(0.000064)**	(0.000018)
W_Leverage	-0.0034	-0.0050		
	(0.00207)*	(0.00123)***		
W_ROA	0.0009	0.0019		
	(0.00073)	(0.00070)***		
Constant		0.01		0.01
		(0.0022)***		(0.00143)***
Including month effects	Yes	Yes	Yes	Yes
Number of observations	1,936	1,936	1,850	1,850
R-sq	0.244	0.276	0.160	0.304

Robust standard errors computed using GMM-HAC in parenthesis.
*, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

The network effects, provoked by the leverage ratio (in MEC) and institution's size (in OTC), are significant at 1% and 5%, respectively, but exert counterintuitive effects on the borrowing cost.

5.2.2 Weights based on assets

The results obtained from spatial models with the contiguity weight matrix could however be overlooking the effects that the intensity of relationship (proximity) between financial institutions may have on the liquidity obtained through sell/buy-backs. The symmetry in this weight matrix implies that all financial institutions within a group are regarded as equal, which may not necessarily be true. In fact, the spatial econometrics literature has recognized that a binary weight matrix may not properly represent the spatial dependence (Hallack and Elhorst, 2015). Accordingly, we evaluate whether the degree of intensity of ownership links may have a say in this context, constructing an alternative weight matrix with elements corresponding to the share that each institution has in the total assets of the group to which it belongs. Also, this weights matrix is time invariant, that is, we are assuming that the intensity of relationships between institutions within the same group can be modelled using the average total assets for the entire period. To obtain these weights, we transform the monthly values of total assets per institution to constant prices using the consumer price index. With this information, we compute the average total assets per financial group for the entire period and the relative participation of each institution within its group. The resulting matrix is not symmetric because the effect of institution i on institution j (both belonging to the same group) differs from the effect of institution j on institution i. Comparing the asset-based weights depicted on Figures 5 with the binary weights (Figure 4), the patterns are naturally the same, but the intensity of interactions (weights) differs.

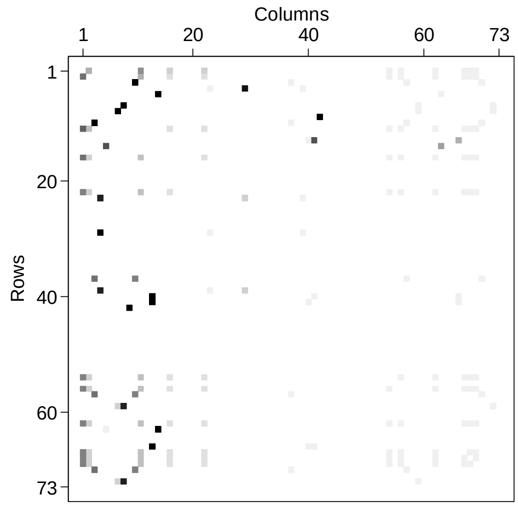

Figure 5. The weight matrix based on assets. This weight matrix differentiates the financial institutions by their owners' group. Those belonging to a group receive a non-zero weight, specified as a function of their percentage participation in the total value of assets of the group they belong. The institutions not related to any group get a zero weight. In this matrix the institutions within a group are not considered as equal, they are differentiated by their relative size defined by their participation in the assets of the group.

As in Section 5.2.1, spatial specifications estimated with this asset-based weight matrix indicate the absence of network effects coming from the dependent variable, which rules out the possibility that the quantity and price of liquidity are determined at a group's level. Moreover, this specification discards the existence of feedbacks effects (global spillovers), indicating that changes at group's level do not impact financial institutions outside the group.

Table 5. SLX model for Liquidity

	MEC	MEC	OTC	OTC
	Fixed effects	**Random effects**	**Fixed effects**	**Random effects**
Spread	-54.93	-38.65	-42.09	-56.25
	(12.39)***	(17.62)**	(11.22)***	(13.17)***
Institution's size	0.2239	-0.1238	0.9560	-0.0127
	(0.1104)**	(0.0369)***	(0.1373)***	(0.0341)
ROA	-0.2915	0.5152	0.4228	0.6315
	(0.2283)	(0.1315)***	(0.4133)	(0.3644)*
Leverage	3.16	3.18	0.6663	2.58
	(0.3752)***	(0.2749)***	(0.4746)	(0.2920)***
W_Institution's size	0.13603	-0.04	0.1537	-0.01
	(0.0387)***	(0.0065)***	(0.0391)***	(0.0077)
Constant		23.74		22.52
		(0.5174)***		(0.4996)***
Including month effects	Yes	Yes	Yes	Yes
Number of observations	1,936	1,936	1,850	1,850
R-squared	0.354	0.283	0.231	0.199

Robust standard errors computed using GMM-HAC in parenthesis.

*, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

The direct effects on the quantity side for semi-anonymous agreements (MEC) stay the same: they are given by the interest-rate spread, the institution's size, and the leverage ratio, while for transactions OTC they depend on the first two (Table 5.1).[12] The cost effect in the amount obtained (-54.9 units in MEC and -42.1 in OTC) suggests that, holding all else equal, the amount of liquidity obtained with sell/buy-backs will fall when this liquidity source gets more expensive. After all, financial institutions can also meet their liquidity needs with repos and interbank loans. A positive marginal effect is observed from institution's size confirming the advantages that larger market participants may attain in terms of funding. For agreements conducted in MEC, this effect along with the leverage ratio suggest, as expected, that larger and more leveraged institutions will seek more liquidity.

The indirect effect from ownership networks comes from the group's size (W_institution's size), with an average marginal effect of 0.044 in MEC and 0.050 in OTC, indicating that institutions that belong to larger financial groups obtain more liquidity. The average overall effect (the sum of the direct and indirect impacts) induced by institution's size will be of .268 for MEC and 1.0 for transactions over-the-counter. The positive average effect exerted by a unit increase in the assets size (from the institution under study and its financial group) will favor even more the largest institutions (0.3599 in MEC 1.10 in OTC) than the smallest ones (0.238 and 0.972, respectively), a result that underlines the role that the institution's relative size plays in this market. The noticeable difference between the average, maximum, and minimum suggests that this effect varies considerably depending on the degree of intensity in institution's relationships defined by their share in group's assets. Finally, note that the direct effect of this variable applies to all institutions participating in sell/buy-backs market whereas the indirect effect will only affect institutions within each group (spill-over effect).

The spatial panel models for the borrowing cost also provide an interesting perspective of these agreements (Table 6). These results, also obtained from a local spillover specification, coincide in that the effects from traditional determinants are the same (i.e., for MEC given by the amount of liquidity, institution's size, and financial leverage, and for OTC given by the liquidity amount).

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[12] The direct effects in the SLX model (own-partial derivative) is the same estimated parameter or own-effect $(\partial R_i/(\partial X_{ik})) = \beta$, while the indirect effects (cross-partial derivative) linearly depend on the weights-matrix: $(\partial R_i/(\partial X_{jk})) = W\theta$ (LeSage, 2014).

Table 5.1 Marginal Effects for liquidity amount

	MEC		OTC	
	Direct effect	Indirect effects	Direct effect	Indirect effects
Interest rate spread	-54.93		-42.09	
	(12.40)***		(11.23)***	
Institution's size	0.2239		0.9560	
	(0.1104)**		(0.1373)***	
ROA	-0.2915		0.4228	
	(0.2283)		(0.4133)	
Leverage	3.16		0.6663	
	(0.3753)***		(0.4746)	
Average W_Institution's size		0.0444		0.0501
		(0.00171)***		(0.0019)***
Max W_Institution's size		0.1360		0.1537
		(0.00526)***		(0.0060)***
Min W_Institution's size		0.0148		0.0167
		(0.00057)***		(0.0065)***

** and *** denote statistical significance at the 5% and 1% levels, respectively.

Although the marginal effects are very small, see Table 6.1, most of them are significant at 1% and 5%. In MEC as well as in OTC, the liquidity amount exerts a negative direct effect on the borrowing cost. All else equal, a unit increase in the amount borrowed will reduce the borrowing cost in 0.03% in the former, and 0.02% in the latter, which indicates that institutions seeking more sizable loans will be charged lower rates. The same negative marginal effect is identified from institution's size in agreements contracted in MEC (0.109%), which validates the well-known negative relationship between the cost of liquidity and the institution's size (i.e., larger financial institutions usually have access to funding at a lower cost).

Table 6. SLX model for the borrowing cost

	MEC	MEC	OTC	OTC
	Fixed effects	Random effects	Fixed effects	Random effects
Liquidity	-0.000302	-0.000110	-0.000202	-0.000169
	(0.00011)***	(0.000081)	(0.00007)***	(0.000049)***
Institution's size	-0.001095	-0.000537	-0.000028	-0.000553
	(0.00038)***	(0.000054)***	(0.00030)	(0.0000408)***
ROA	-0.000124	-0.000017	-0.000913	-0.003260
	(0.00061)	(0.000302)	(0.00127)	(0.000805)***
Leverage	0.002564	0.001465	0.000381	0.001626
	(0.00106)***	(0.000406)***	(0.00112)	(0.00046)***
W_ROA	-0.003688	-0.002295	-0.003006	-0.001875
	(0.00166)**	(0.0021)	(0.00152)**	(0.00103)*
Constant		0.01005		0.01270
		(0.00226)***		(0.00138)***
Including month effects	Yes	Yes	Yes	Yes
Number of observations	1,936	1,936	1,850	1,850
R-sq	0.243	0.260	0.159	0.303

Robust standard errors computed using GMM-HAC in parenthesis.
*, ** and, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

For agreements in the MEC system, the disadvantages of a high leverage level are also visible in our results. In this regard, the model predicts that a unit increase in the leverage ratio will rise the liquidity price by 0.25%. In other words, this result implies that financial institutions may end up getting costly liquidity when their leverage level (financial performance) raises lenders' concerns regarding their ability to repay loans.

The ownership network effect of profitability on contracts agreed semi-anonymously (MEC) will reduce the borrowing cost in 0.12%, hence indicating that the institution under study will face lower funding costs when it makes part of a more profitable group (W_ROA). For the largest institution in the group, this effect will represent an average reduction of 0.36% while for the smallest participant that reduction will be equal to 0.04%.

For OTC contracts, the group effects are also provoked by W_ROA. The indirect effects induced by group's average profitability generates local spillovers that lessen the funding rates charged to institutions within the group. As in the liquidity model, this effect is amplified by the institution's shares on the group's assets, and given its negative sign, it tends to reduce the funding rates in 0.0074%. Once more, such reductions will be lower for the smaller institutions (-0.010%) than for the largest ones (-0.091%).

Table 6.1 Marginal Effects for the borrowing cost

	MEC		OTC	
	Direct effect	Indirect effects	Direct effect	Indirect effects
Liquidity	-0.00030		-0.00020	
	(0.00011)***		(0.000079)***	
Institution's size	-0.00109		-0.00003	
	(0.00039)***		(0.00031)	
ROA	-0.00012		-0.00091	
	(0.00061)		(0.00127)	
Leverage	0.00256		0.00038	
	(0.00106)***		(0.00113)	
Average W_ROA		-0.00123		-0.00030
		(2.05E-0.6)**		(4.64E-0.7)**
Max W_ROA		-0.00040		-0.00010
		(6.68E-0.7)**		(1.51E-0.7)**
Min W_ROA		-0.00369		-0.00091
		(6.13E-0.6)**		(1.39E-0.6)**

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

From the estimation point of view, the gains from using an alternative weight matrix, which differentiates institutions by their relative sizes, are small in this context as they lead to similar results. Nevertheless, they confirm the main conclusions obtained from specifications when all institutions in the financial group are regarded as equal, which corresponds to the previously used weight matrix assigning the same weight to each institution in the group.

Furthermore, the fact that the models that best describe this segment of the money market reveal that spillover effects are local, which implies that changes at group's level do not impact financial institutions outside the group (there are no higher-order neighbors), because there is no link between them. In other words, the absence of financial group's participation in other corporate groups do not support the existence of more complex relationships, such as that described by cross-shareholdings (see Glattfelder, 2010). The relationship structures specified for financial groups describe ownership links that cause only within-group effects. Hence, the ownership networks effects will impact only the institutions belonging to the same group, especially those with a sizable participation in their total assets. This last result implies that the institutions within a group are not regarded as equal, and hence, the last set of models properly capture the effects provoked by ownership networks. These results support our premise that group's effects are relevant determinants of the amount and cost of liquidity in the sell/buy-backs market, even considering the differences that may arise from contracts agreed in a semi-anonymous way and over-the-counter.

5.3 Some robustness checks

To test our results we conducted three robustness checks. First, we test the validity of the weight matrix based on assets, for which we evaluate the residuals of the preferred specifications. We find that the fraction of pairs of financial institutions that contain correlated residuals is lower than 1% (cf. Table B4 in the Appendix). Hence, the validity of the spatial models is verified by the regression analysis (the condition of independence of residuals is met in all specifications) and they remain valid from a theoretic point of view as well (the relevancy of the traditional determinants of this market and their ownership networks effects). Overall, these results rule out the existence of spatial correlation in the residuals. The second robustness check consisted in estimating the models excluding the market participants that resort less to sell/buy-backs (pension funds and commercial finance companies). The results obtained from excluding them do not generate substantial changes in the estimated coefficients (tables B5 and B6). Finally, we considered alternative thresholds to determine whether there are further agreements contracted with the purpose to obtain liquidity. The rationale behind this robustness check is explained as follows. The central bank offers financial institutions a deposit facility (in the form of unsecured deposits) to absorb excess liquidity at a rate equivalent to 100 basis points (bp) below the policy rate. Therefore, intuitively, financial institutions with liquidity surpluses should be eager to lend to other financial institutions at some rate above the policy rate minus 100 bp threshold; at equal or lower rates, they should prefer to deposit their surpluses at the central bank. Consequently, as the rate that excludes security-driven agreements (buy/sell-backs) should depend on the unobservable rate at which financial institutions are indifferent between lending to other financial institutions and making a deposit at the central bank, we considered alternative rate thresholds (i.e. policy rate minus 10, 50 and 100 bp) to study whether results are robust to our choice for filtering out non-liquidity-driven transactions. The main results are the same with the policy rate and the policy rate minus 10 bp. However, as we move farther from the equality between the policy rate and sell/buy-backs rate (50 and 100 bp), models capture less of the relevant traditional determinants (i.e. the price-quantity relationship becomes positive), especially in OTC transactions (tables B7 and B8). In other words, larger reductions in the threshold may possibly allow the presence of more securities-driven agreements (buy/sell-backs) in data. Therefore, as expected, we verify that results are robust to non-large reductions in the threshold, whereas large reductions appear to allow agreements that pursue securities –but not liquidity.

6. Conclusions

Financial institutions meet their liquidity needs using their own deposits at the central bank, the payments received from their counterparties, or raising funds in the money markets (through secured or unsecured loans). The secured borrowing (in term of its quantity and price) using sell/buy-backs depends on traditional determinants like the institution's size and financial leverage, but also on the network effects defined as pertaining or not to a financial group. As our results indicate, these effects provide a more comprehensive view of this market. On the quantity side we found a network effect caused by the average size of the financial group, while on the cost side this effect depend on the average group's profitability.

However, as usual in this type of models, the obtained results are particular to the specified matrix of spatial weights. Therefore, possible extensions to this topic could include the evaluation of other weight matrices defining other relationships. In this regard, it would be interesting to consider the literature of social interactions to evaluate alternative relationships. Another interesting extension could be to specify dynamic weight matrices that allow the formal evaluation of changes in the relative importance of financial institutions across time.

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Appendix A - The model of Bester (1985)

The model proposed by Bester (1985) assumes the existence of one good (money), two dates (t=0 and t=1), two states of nature (s) and a group of agents (a lender bank and several borrowers) that consume only at date 1. The nature determines the borrower's type (good type (α) or bad type (β)), but this is private information because only each one of them knows its true type. Every borrower has the opportunity to undertake a project that requires an investment in t=0 that will produce a random return y_s at time t=1. He is planning to finance the investment borrowing from the bank an amount B that he commits to repay along with the interest payments rB at t=1. The investment can be successful ($y_s=y$) or not ($y_s=0$), the chance of which is represented by a risk parameter π^i that measures the probability of project failure and depends on the state of the nature in the future and the borrower's type (the superscript *i* corresponds to α for the low-risk borrowers and β for the borrowers with a high risk).

The model assumes that the lender and borrowers are represented by risk neutral preference-scaling functions $\upsilon(y_s)$ and are maximizers of expected utility functions $[E\{\upsilon(y_s;\ \pi)\}]$ of Von-

Neumann Morgenstern type.[13] The information asymmetry arises from the fact that the bank is not able to observe the risk parameter π^i, which may cause a problem of adverse selection in the allocation of credits. For simplicity, let $\pi(s)$ represents a probability density function such that $\int\pi(s)\, ds=1$.

For the ith borrower, the expected benefit from a given contract (γ), denoted as $U_i(\gamma)$, depends on two state-contingent claims:

$$U_i(\gamma) = (1 - \pi^i)[y - (1 + r)B - kC] + \pi^i[0 - C - kC]. \qquad \text{(A.1)}$$

If the borrower's project is successful, he will get the remaining income after paying back to the bank the loan and the interests ((1 + r) B), but if the project fails, he will lose the collateral (C). In any of the cases, the borrower will have to incur in a cost of collateralization ($k \geq 0$) that depends linearly on the collateral value (kC).

The expected benefits for the bank from granting a loan γ to a particular borrower are given by:

$$\rho_i(\gamma) = (1 - \pi^i)[(1 + r)B - B] + \pi^i[C - B]. \qquad \text{(A.2)}$$

The first term represents success in the borrower's investment project ($y_s=y$), in which case the bank will get an income equal to the interest payments. The second term corresponds a failure in the investment project ($y_s=0$), representing for the bank a revenue given by the difference between the market value of collateral (the bank liquidates the collateral) and the loan granted. Given that the model assumes the bank has all the bargaining power regarding the terms of the loan contracts, it maximizes its expected benefits in the credit market ($\rho(\gamma)$) subject to the individual rationality constraints (defined by (A.1) and the respective borrower's reservation utilities $\underline{U}^i$) and the incentive compatible constraints (A.3) and (A.4):

$$U_\alpha(\gamma_\alpha) \geq U_\alpha(\gamma_\beta), \qquad \text{(A.3)}$$

$$U_\beta(\gamma_\beta) \geq U_\beta(\gamma_\alpha). \qquad \text{(A.4)}$$

The borrower's marginal rate of substitution between the rate r of interest charged for a loan and collateral requirements C for a given contract γ, $\sigma_i(\gamma) = dr/dC = -[(\pi^i+k)/(1-\pi^i)B]$, is related negatively to the ratio of the marginal utility-of-income for each state of the world. Thus, under

[13] The assumption of risk-neutral agents makes sense in this context because banks rely on large and diversified portfolios represented by several loans, risk-averse agents, instead, correspond to banks with few loans that may imply high risks (Freixas and Rochet, 2008).

the assumption that the risky borrowers have a risk of failure higher than the low-risk borrowers ($\pi^{\beta} > \pi^{\alpha}$), those with the low risk will have a marginal rate of substitution higher, $\sigma_{\alpha}(\gamma) > \sigma_{\beta}(\gamma)$, which indicates that they are more willing to accept an increase in collateral requirements in exchange for a reduction in the interest rate. Similarly, the marginal rate of substitution for the bank offering loans for a particular borrower type will be equal to $\mu_i(\gamma) = dr/dC = - \pi^i/(1 - \pi^i)B$. The optimal solution implies the bank overcomes the problem of adverse selection by specifying different contracts ($\gamma_{\alpha}^* \neq \gamma_{\beta}^*$) for each type of borrower, using collateral requirements and interest rates as self-selection mechanisms. In this way, the borrowers end up revealing their true type when they choose a particular contract: those of the high risk will be more willing to prefer contracts with a high interest rate and low collateral requirements, whereas those of the low risk will accept contracts with the opposite combination.

This separating equilibrium is possible under the assumption that banks, when offering a credit, determine the rate of interest and collateral requirements simultaneously. This solution does not produce a credit rationing in the sense that only some borrowers can get loans, but it rather describes a menu of contracts, where different combinations of collateral requirements and interest rates are used as self-selection mechanisms. However, this solution requires two necessary conditions: the existence of a monotone relationship between the borrower's riskiness and preferences, and the willingness of low risk borrowers to provide a sufficient amount of collateral (see Bester, 1985).

Appendix B

Table B1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Liquidity (in natural logarithms) MEC	2,087	23.86	1.87	16.18	29.23
Liquidity (in natural logarithms) OTC	1,855	24.18	1.87	16.68	29.09
Interest rate spread, MEC	2,087	0.003	0.003	0.00	0.055
Interest rate spread, OTC	1,855	0.002	0.004	0.00	0.049
Institution's size (natural logarithm of total assets)	5,718	12.84	2.63	7.56	18.57
ROA	7,008	-0.04	0.502	-15.20	0.849
Financial leverage (Total Liabilities/Total Assets)	5,718	0.556	0.313	0.002	0.969

Table B2. White tests for Heteroskedasticity for fixed effect models

Models for Liquidity		F-test	P-value
Liquidity_MEC	F(154, 1781)	4.08	(0.000)
Liquidity_OTC	F(152, 1697)	3.87	(0.000)
Models for Spread		**F-test**	**P-value**
Spread_MEC	F(154, 1781)	7.57	(0.000)
Spread_OTC	F(152, 1697)	11.74	(0.000)

Table B3. Endogeneity tests for fixed effect models

Models for Liquidity		Regressors tested for endogeneity	GMM C statistic Chi2(1)	P-value
MEC	Linear panel data model	Spread_MEC	1.69	(0.193)
OTC	Linear panel data model	Spread_OTC	0.46	(0.499)
MEC	SLX model with a (0/1)W	Spread_MEC	1.53	(0.216)
OTC	SLX model with a (0/1)W	Spread_OTC	0.44	(0.508)
MEC	SLX model with an assets' based W	Spread_MEC	2.03	(0.154)
OTC	SLX model with an assets' based W	Spread_OTC	0.50	(0.480)
Models for Spread		**Regressors tested for endogeneity**	**GMM C statistic Chi2(1)**	**P-value**
MEC	Linear panel data model	Liquidity_MEC	3.28	(0.070)
OTC	Linear panel data model	Liquidity_OTC	1.17	(0.278)
MEC	SLX model with a (0/1)W	Liquidity_MEC	3.43	(0.064)
OTC	SLX model with a (0/1)W	Liquidity_OTC	1.18	(0.277)
MEC	SLX model with an assets' based W	Liquidity_MEC	3.27	(0.070)
OTC	SLX model with an assets' based W	Liquidity_OTC	0.95	(0.328)

The GMM C test is used to check whether a subset of regressors satisfies the orthogonality condition (i.e., they are uncorrelated with the error term). Under the null hypothesis of exogeneity, this test is distributed as χ^2 with degrees of freedom equal to the number of conditions (Hayashi, 2000).

Table B4. Fraction of non-zero covariances on the residuals
(Using a weights matrix based on assets)

		Fraction of non-zero covars
Model for liquidity, MEC	Fixed-effects SLX model	0.0092
Model for liquidity, OTC	Fixed-effects SLX model	0.0098
Models for the borrowing cost, MEC	Fixed-effects SLX model	0.0062
Models for the borrowing cost, OTC	Fixed-effects SLX model	0.0069

Table B5. Excluding pension funds and commercial finance companies
Models for Liquidity (Using a weights matrix based on assets)

	MEC	MEC	OTC	OTC
	Fixed effects	Random effects	Fixed effects	Random effects
Spread	-52.03	-39.85	-43.87	-58.59
	(12.65)***	(17.19)**	(11.16)***	(13.09)***
Institution's size	0.2358	-0.1467	0.9301	-0.0255
	(0.1111)**	(0.0369)***	(0.1382)***	(0.0347)
ROA	-0.3192	0.4944	0.4677	0.5728
	(0.2284)	(0.1264)***	(0.4124)	(0.3661)
Leverage	3.14	3.49	0.7272	2.78
	(0.3768)***	(0.2731)***	(0.4758)	(0.3011)***
W_Institution's size	0.13750	-0.04	0.1504	-0.01
	(0.0385)***	(0.0065)***	(0.0389)***	(0.0078)
Constant		24.09		22.59
		(0.4868)***		(0.5010)***
Including month effects	Yes	Yes	Yes	Yes
Number of observations	1,894	1,894	1,819	1,819
R-squared	0.3623	0.3158	0.2297	0.2065

Robust standard errors computed using GMM-HAC in parenthesis.

*, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table B6. Excluding pension funds and commercial finance companies
Models for interest rate spread (Using a weights matrix based on assets)

	MEC	MEC	OTC	OTC
	Fixed effects	Random effects	Fixed effects	Random effects
Liquidity	-0.000292	-0.000116	-0.000202	-0.000169
	(0.00011)***	(0.000085)	(0.000079)***	(0.000049)***
Institution's size	-0.001096	-0.000549	-0.000028	-0.000553
	(0.00039)***	(0.000055)***	(0.00030)	(0.000040)***
ROA	-0.000085	-0.000041	-0.000913	-0.003260
	(0.00061)	(0.000303)	(0.00127)	(0.000805)***
Leverage	0.002536	0.001604	0.000381	0.001626
	(0.00107)***	(0.000424)***	(0.001124)	(0.000468)***
W_ROA	-0.003596	-0.002440	-0.003006	-0.001875
	(0.00166)**	(0.00210)	(0.00152)**	(0.00103)*
Constant		0.01037		0.01270
		(0.00236)***		(0.00138)***
Including month effects	Yes	Yes	Yes	Yes
Number of observations	1,894	1,894	1,819	1,819
R-sq	0.236	0.257	0.159	0.303

Robust standard errors computed using GMM-HAC in parenthesis.

*, ** and, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table B7. Robustness check- 50 and 100 basis points below the policy rate Models for Liquidity (Using a weights matrix based on assets)

	50 basis points	50 basis points	100 basis points	100 basis points
	MEC	OTC	MEC	OTC
	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Spread	-39.99	6.58	-27.66	20.11
	(15.29)***	(14.52)	(15.21)*	(12.40)
Institution's size	0.2693	0.9994	0.3257	0.9874
	(0.1078)***	(0.1319)***	(0.1119)***	(0.1251)***
ROA	-0.2558	-0.2428	-0.3275	-0.4789
	(0.2554)	(0.3703)	(0.2652)	(0.3693)
Leverage	3.66	1.4068	3.51	1.5744
	(0.3776)***	(0.4986)***	(0.3840)***	(0.4670)***
W_Institution's size	0.06611	0.0180	0.02995	0.0142
	(0.0375)*	(0.0286)	(0.0362)	(0.0259)
Including month effects	Yes	Yes	Yes	Yes
Number of observations	2,391	2,359	2,478	2,448
R-squared	0.283	0.250	0.275	0.273

Robust standard errors computed using GMM-HAC in parenthesis.

*, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table B8. Robustness check- 50 and 100 basis points below the policy rate Models for interest rate spread (Using a weights matrix based on assets)

	50 basis points	50 basis points	100 basis points	100 basis points
	MEC	OTC	MEC	OTC
	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Liquidity	-0.000175	-0.000068	-0.000159	0.000110
	(0.00009)*	(0.000043)	(0.00010)	(0.0000645)*
Institution's size	-0.001382	-0.000599	-0.001465	-0.000131
	(0.00042)***	(0.000039)***	(0.000453)***	(0.000342)
ROA	-0.000270	-0.003166	-0.000414	0.000837
	(0.00060)	(0.000794)***	(0.00064)	(0.00147)
Leverage	0.003083	0.000173	0.003090	-0.000593
	(0.001151)***	(0.000428)	(0.00129)**	(0.00119)
W_ROA	-0.003647	-0.001176	-0.001261	-0.000463
	(0.00122)***	(0.000633)*	(0.00218)	(0.00076)
Including month effects	Yes	Yes	Yes	Yes
Number of observations	2,391	2,359	2,478	2,477
R-sq	0.303	0.376	0.364	0.265

Robust standard errors computed using GMM-HAC in parenthesis.

*, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.